Association Analysis

- Given a set of transactions, find rules that will predict the occurrence of an item based on the occurrence of other items in the transaction.
- Called sometimes Market Basket Analysis.



Examples

- On Thursdays, grocery store consumers often purchase diaper and beer together.
- Customer who purchase maintenance agreements are very likely to purchase large appliances.
- When a new hardware store opens, one of the most commonly sold item is toilet ring.

These three examples illustrate the three common types of rules produced by market basket analysis: the *useful*, the *trivial*, and the *inexplicable*.

- Once the pattern is found, it is often hard to justify. Even if justified, the results would not be useful.
 - The useful rule contains high quality, actionable information.
 The first example provides and justifiable(high quality), and actionable information.
 - Trival results are already known by anyone at all familiar with the business
 - In fact, we already know that customers purchase maintenance agreements and large appliances at the same time.
 - Inexplicable results seems to have no explanation and do not suggest a course of action.
 - It is doubtful that further analysis of just the market basket data can give a credible explanation.
- Trivial and Inexplicable Rules occur most often

How Does Market Basket Analysis Work

- Market Basket analysis start with transactions containing one or more products or service offering and some rudimentary information about the transaction.
- Each of these transaction gives us information about which products are purchased with which other products.

Grocery store transactions

| Customer | items |
|----------|------------------------------------|
| 1 | orange juice, soda |
| 2 | milk, orange juice, window cleaner |
| 3 | orange juice, detergent |
| 4 | orange juice, detergent, soda |
| 5 | window cleaner, soda |

Co-occurrence Table

| | | Window | | | |
|----------------|----|---------|------|------|-----------|
| | OJ | Cleaner | Milk | Soda | Detergent |
| OJ | 4 | 1 | 1 | 2 | 1 |
| Window Cleaner | 1 | 2 | 1 | 1 | 0 |
| Milk | 1 | 1 | 1 | 0 | 0 |
| Soda | 2 | 1 | 0 | 3 | 1 |
| Detergent | 1 | 0 | 0 | 1 | 2 |

- Orange juice and soda are more likely to be purchased together than any other two item.
- Detergent is never purchased with window cleaner or milk.
- Milk is never purchased with soda or detergent.

 These simple observations are examples of associations and may suggest a formal rule like:

"If a customer purchases soda, then the customer also purchases milk."

- The question is how good is the rule?
- Support and Confidence.
 - Two of the five transactions include both soda and orange juice.
 These two transactions support the rule. i.e, the support for the rule is two out of five or 40%.
 - Every transaction that contains soda also contains orange juice, the rule has a confidence 100%.
 - However, the inverse rule, "if orange juice than soda," among 4 transactions with orange juice, only two also have soda. Thus, its confidence is 50%.

If A then B

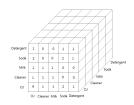
Formally the support and the confidence are defined as follow:

- Support is defined as $\Pr(A \cap B)$ where the probability is the proportion of transactions contain both A and B among all transactions.
- ullet While, confidence is defined as $\Pr(A \cap B)/\Pr(A) = \Pr(B|A)$

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The Problem of Big Data

- The ideas behind the co-occurrence table extend to any combinations with any number of items, not just pairs of items.
- e.g, For combinations of three items, imagine a cube with each side split into five different parts.
- The 3-D co-occurrence table may produce rules such as "if A and B then C" or "if A then B and C."
- However, the number of combinations of a given size tends to grow exponentially.



• Suppose that a fast-food restaurant offers several dozen items on its menu, say there are a 100.

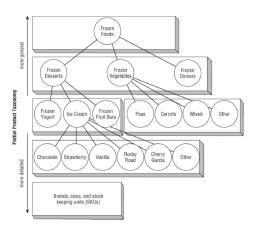
The number of combinations of items

| # in combination | # of combinations |
|------------------|-------------------|
| 1 | 100 |
| 2 | 4,950 |
| 3 | 161,700 |
| 4 | 3,921,225 |
| 5 | 75,287,520 |
| 6 | 1,192,052,400 |
| 7 | 16,007,560,800 |
| 8 | 186,087,894,300 |

Choosing the Right Set of Items

- A grocery store may have tens of thousands of products on the shelves.
- Suppose a frozen pizza might be considered an item for analysis purposes—regardless of its toppings, its crust, or its size.
- So, the purchase of a large whole wheat vegetarian pizza contains the same frozen pizza.
- On the other hand, the manager of frozen foods may be very interested in the particular combinations of toppings that are ordered.
- Choosing the right level of detail is a critical consideration for the analysis.
- In the real world, items have product codes and stock-keeping unit codes that fall into hierarchical categories, called taxonomy.
- What level of taxonomy is the right one to use?

Taxonomies start with the most general and move to increasing detail



Generating Rules

 A rule has two parts, a condition and a result. If condition, then result.

If 3-way calling, then call-waiting

- In practice, the most actionable rules have just one item as the result.
 - "If diapers and Thursday, then beer", is more useful than "If Thursday, then diapers and beer."
- Thus, with 3 items A, B and C, the only rules to consider are:
 - If A and B, then C.
 - If A and C, then B.
 - If B and C, then A.

Probabilities of three items and their combinations

| Combination | Probability |
|---------------|-------------|
| A | 45% |
| В | 42.5% |
| C | 40% |
| A and B | 25% |
| A and C | 20% |
| B and C | 15% |
| A and B and C | 5% |
| | |

Confidence in Rules

| Rule | P(condition) | P(condition and result) | Confidence |
|-------------------|--------------|-------------------------|------------|
| If A and B then C | 25% | 5% | 0.20 |
| If A and C then B | 20% | 5% | 0.25 |
| If B and C then A | 15% | 5% | 0.33 |

- The most confidence rule is the best rule, so we are tempted to choose "If B and C, then A."
- But there is a problem. The rule is actually worse than if just randomly saying that A appears in the transaction.
- A occurs in 45% of the transactions but the rule only gives 33% confidence.
- This suggests another measure called improvement.
- Improvement tells how much better a rule is at predicting the result than just assuming the result in the first place.

$$improvement = \frac{P(condition \ and \ result)}{P(condition)P(result)} = \frac{confidence}{P(result)}$$

The improvement is similar to the Lift.

Improvement Measurement

| Rule | Support | Condition | Improvement |
|-------------------|---------|-----------|-------------|
| If A and B then C | 5% | 20% | 0.50 |
| If A and C then B | 5% | 25% | 0.59 |
| If B and C then A | 5% | 33% | 0.74 |
| If A then B | 25% | 59% | 1.31 |

- When improvement is greater than 1. then the resulting rule is better at predicting the result than random chance.
- None of the rules with three items shows any improvement.
- The rule "If A then B" is the best rule in the data.

Negating Rules

 When improvement is less than 1, negating the result produces a better rule.

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If the rule
    "If B and C, than A"
has a confidence of 0.33, then the rule
    "If B and C, then, NOT A"
has a confidence of 0.67, and the new rule has an improvement of 1.33.
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- When the improvement score is low, it can increase them by negating the rules.
- However, negating rule may not be useful.

Minimum Support Pruning

- As the number of items in the combinations are growing, it requires heavy computation works.
- Thus, when then number of items are large, we need *pruning*.
- The most common pruning method employed in the association analysis is minimum support pruning. That is, a rule should hold on a minimum number of transactions.
- e.g., if there are 1 millon transactions and the minimum support is 1 percent, then only rules supported by 10,000 transactions are of interest.
- i.e., minimum support pruning eliminates items that do not appear in enough transactions.
- There are two ways to do this.
 - Eliminate the items from consideration.
 - Use the taxonomy to generalize the items so the resulting generalized items meet the threshold criterion.

Other Applications

- Baskets = documents
- Items = words in those documents
 - Find word that apper together unusually frequently, i.e., linked concepts.

| | Word 1 | Word 2 | Word 3 | Word 4 |
|-------|--------|--------|--------|--------|
| Doc 1 | 1 | 0 | 1 | 1 |
| Doc 2 | 0 | 0 | 1 | 1 |
| Doc 3 | 1 | 1 | 1 | 0 |

Work $4 \Longrightarrow Word 3$

Other Applications

- Baskets = sentences
- Items = documents containing those sentences
 - Sentences that appear together too often could represent plagiarism,

| | Doc 1 | Doc 2 | Doc 3 | Doc 4 |
|--------|-------|-------|-------|-------|
| Sent 1 | 1 | 0 | 1 | 1 |
| Sent 2 | 0 | 0 | 1 | 1 |
| Sent 3 | 1 | 1 | 1 | 0 |

$$Doc 3 \Longrightarrow Doc 4$$

Other Applications

- Baskets = Web pages
- Items = linked pages
 - Pairs of pages with many common references may be about the same topic.
- Baskets = Web pages p_i
- Items = pages that link to p_i
 - Pages with many of the same links may be mirrors or about the same topic.

| | wp a | wp b | wp c | wp d |
|-----|------|------|------|------|
| wp1 | | | | |
| wp2 | | | | |

Reference

• Data Mining Techniques: For Marketing, Sales, and Customer Support, Michales J. A. Berry and Goron Linoff